Application Analysis of Multi-Task Learning Algorithm in E-Commerce Personalized Advertising Intelligent Push

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Abstract: *To improve the precision of personalized selection and push of e-commerce advertising content, a personalized advertising recommendation model based on improved Multi-Task Learning (MTL) algorithm is proposed. This study uses the data set of Specific Feature keywords (SFs) clicked by users and the basic facts of users' preference for selling keywords to increase the click-through rate of advertisements by adding personalized selling keywords in the advertisement title. Combined with the click-through rate prediction task as an auxiliary task, the prediction ability of the model is enhanced. Experimental results show that the model is better than the traditional method in terms of click-through rate, recommendation accuracy and efficiency. The Area Under the Curve (AUC) value of the model reaches 0.92, which is significantly improved compared with 0.81 of the traditional models, and the recommendation efficiency is increased by 14.26%. Through large-scale online and offline experiments, the superiority of the model in several indexes is verified. The model is particularly suitable for scenarios where users have rich clicking behavior in auxiliary tasks but sparse clicking behavior in main tasks. This study provides an effective method for optimizing the advertising push of e-commerce platforms.*

Keywords: *MTL algorithms, selling point keywords, sponsored search, click through rate, electronic business, advertisement, recommended.*

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1. Introduction

With the booming development of modern technology, online shopping has become an essential part of many people's daily lives. And with the rapid spread of mobile devices, more and more people are choosing to use more convenient mobile devices to access e-commerce platforms [35]. In order to increase the sales revenue of online merchants and maximise the benefits of the e-commerce platform, most e-commerce websites have introduced the Sponsored Search (SS) mechanism and concept in the traditional search engine [5]. In SS, advertisers bid on query terms and when a user makes a request for a query term, the bidding mechanism is triggered and the winning advertised item is displayed in the user's search list and thus presented to the querying user [12]. However, most of the research work in SS has focused on bid optimization and Click-Through-Rate (CTR) prediction, and there is a lack of intelligent optimization of ad content [41]. In the current field of machine learning, the benefits of Multi-Task Learning (MTL) are more prominent, as MTL can improve the effectiveness of each model across multiple tasks, including model learning performance and task prediction accuracy, compared to training a model independently [27]. The study, therefore, proposes a MTL algorithm to build an intelligent recommendation model for personalized e-commerce advertisements by automatically adding personalized Selling Point keywords (SPs) to the advertisement content. The MTL model designed by the research is slightly different from the standard hard sharing model. The multi-task learning model is a customized MTL model for specific problems. Its innovation points are mainly reflected in the following two aspects. First, modules with attentional mechanisms are designed specifically for auxiliary tasks. Second, the two tasks do not share the same input, in other words, the input data sources for the main and secondary tasks are different. We designed a multi-task neural network model to predict personalized attractive SPs tasks given the query terms submitted by users. At the same time, in order to solve the problem that there are few feedback data about users' explicit preferences for SPs, we proposed to use the information of users' clicks on Specific Feature keywords (SFs) as an alternative to the explicit feedback of users' preferences for SPs, and use this data to train the model accordingly. In this paper, CTR predictive task is used as an auxiliary task to construct a MTL model framework and enhance the predictive ability of the main task. Finally, this paper further incorporates a variety of additional features about users and query terms into the basic model of this paper, so that the model learns a more powerful vector representation. The research aims to accurately display the most attractive product features to users to improve their shopping experience and promote their consumption activities.

2. Related Work

With the rapid popularity of mobile devices, more and more people are choosing to use more convenient mobile devices to access e-commerce shopping platforms, thus attracting many scholars from home and abroad to study intelligent recommendations for e-commerce advertisements on mobile. Kang *et al*. [15] proposed a trial recommendation system based on a tree model of user history data in order to achieve personalized ad recommendations. Experiments showed that the system has better recommendation performance. Liu *et al*. [18] proposed an ad recommendation method that integrates fairness and personal interest by studying online banner ads that are usually placed on specific news websites. Experiments show that the method performs better than traditional methods and helps to increase the average CTR of ADS. Bhattacharyya *et al*. [6] scholars studied the effect of likes on Facebook on users' purchase and recommendation decisions on linked e-commerce sites and found that higher likes on Facebook led to a higher likelihood of purchasing and recommending products on linked e-commerce sites. Wu *et al*. [40] proposed a personalized recommendation framework based on the theory of key technologies for video recommendation systems based on user interest graphs. The study showed that the framework has good practicality. García-Sánchez *et al*. [13] proposed an ontology-based recommendation system for advertising using data generated by users in social networking sites and through a shared ontology model. The study shows that the system has good recommendation accuracy.

Table 1. Related worksheets.

Year	Author	Method	Merits and demerits
2019	Liu *et al*. [18]	Combining fairness and personal interest in advertising recommendation methods	The average CTR of advertisements is improved, but the push accuracy is poor
	García-Sánchez *et al*. [13]	Advertising recommendation system based on ontology	The performance of personalized recommendation is poor
	Zhu *et al*. [48]	Personalized recommendation service based on multi-source and multi-task learning	The robustness of this framework is low
2020	Kang *et al*. [15]	Recommendations based on user history data generation tree model	The system has a good recommendation performance, but cannot meet the current forms of various advertising push.
	Bhattacharyya *et al*. [6]	The study found that the number of likes is closely related to the recommended purchase of products	Found that "likes" on online platforms help to attract users' interest
	Wu *et al*. [40]	Personalized inference framework based on user interest graph	The robustness of this framework is low
	Qu and Guo [28]	Recommendation method based on fast discrete factorizer	The recommendation effect is good, and the robustness of the algorithm is low
	Li *et al*. [17]	Personality-assisted multi-task deep learning framework	The recommendation effect of images is good, but it cannot meet the push requirements of keywords
2021	Nitu *et al*. [25]	A recommendation system based on time-sensitive nearest weights	The performance of personalized recommendation is poor
	Liu *et al*. [20]	Recommendation method of collaborative filtering algorithm based on clustering	The robustness of this framework is low

Nitu *et al*. [25] researchers considered users' recent interests by adding time-sensitive recent weights to a traditional recommendation model. Experimental results showed the superiority of the model with an overall accuracy of 75.23%. Qu and Guo [28] proposed a fast-discrete factor decomposer method in order to solve the problem of the limitation of a large number of feature dimensions caused by a large number of personalized product recommendations. The study showed the effectiveness of the method. Liu *et al*. [20] proposed a collaborative filtering algorithm based on clustering to quantify customer preference attributes for personalized recommendation schemes. Experiments show the superiority of the method. Li *et al*. [17] proposed a personality-assisted multi-task deep learning framework for generic and personalized image aesthetics evaluation. The results show that the framework outperforms existing methods for both personalized recommendation tasks. Zhu *et al*. [48] proposes multi-source MTL for user models in social networks, and the study shows that the method can provide accurate personalized recommendations for social users. As shown in Table 1, it is an overview of previous research results.

Based on existing domestic and foreign studies, it is found that the above-mentioned research work mainly focuses on relatively common SS Settings, while this paper focuses on personalized and attractive SPs prediction tasks in SS return results under the background of e-commerce. In previous work, it did not solve the problem of automatic real-time intelligent optimization of advertising content in the SS scenario of the e-commerce platform. And most of them do not consider the preferences of different query users when evaluating the value of attractiveness to users. Therefore, after learning from previous achievements and analysis problems, the research proposes to add SPs to advertising content, and apply multi-task deep learning algorithms to the intelligent push of personalized advertisements on e-commerce platforms.

3. Research on Intelligent Push Method of Personalized Advertising for E-Commerce Based on the Multi-Task Learning Algorithm

This paper proposes a personalized advertising recommendation model based on MTL algorithm, which is used in the intelligent advertising push of e-commerce platform. The model is trained on user click data, using user preferences for SF and SPs to predict what ads they are likely to be interested in CTR, an auxiliary task of MTL, further improves the prediction accuracy of SP. In practice, when the user does a search, the model automatically adds personalized SP to the AD title to optimize the AD content displayed and make it more attractive.

3.1. Design of a Base Model for Smart Pushing of Personalized Ads for E-Commerce Based on Multi-Task Learning Algorithms

MTL has a variety of manifestations and its effectiveness is mainly reflected in the transfer and use of associative information from multiple tasks at the same time to improve the performance of a single task [1, 24]. A schematic of a multitasking neural network with four different tasks for training and learning is shown in Figure 1.

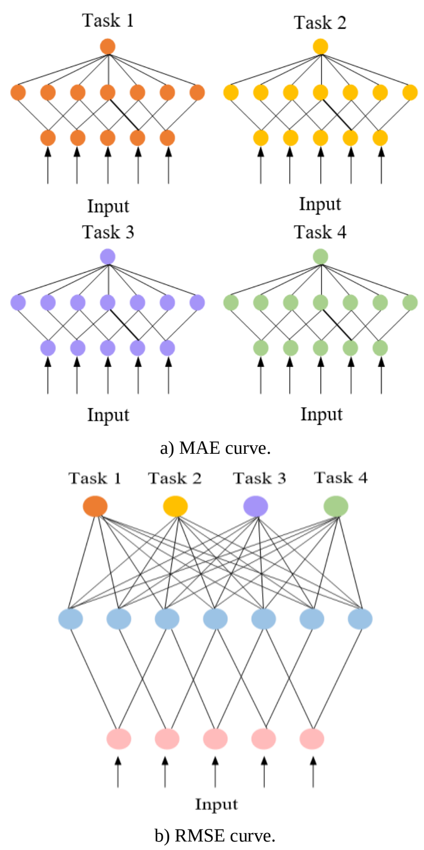


Figure 1. Schematic diagram of four task neural networks.

As can be seen from Figure 1-a), the individual networks receive the same input, but the trainable parameters of the networks are not shared, and the final output results of the tasks are the same. As can be seen in Figure 1-b), when four tasks are trained simultaneously, they share some of the parameters and the output layer parameters remain separate, resulting in shallow feature sharing and information transfer. In general, an MTL can be recognized as long as the optimization model consists of more than one loss function, and there are three main factors that can influence the relevance of the task in existing MTL models, namely the features, parameters, and sample instances [31]. The class is further divided into three approaches, feature transformation, selection, and deep learning, based on how the original features in the task are shared. Firstly, feature transformation methods are used to transform the original features in a linear or non-linear manner [38].

Parameter-based information transfer is mainly used to associate different tasks through model-building parameter interaction and sharing [10]. There are many ways of generating links between multiple models, which are divided into four main approaches: low-rank matrix, task clustering, task linkage learning, and multilevel. Among them, the model parameters of multiple tasks partially share the same low-rank subspace as in Equation (1) [22].

$$w^{(l)} = u^{(l)} + \Theta^{T} v^{(l)} \tag{1}$$

In Equation (1), $w^{(l)}$ represents the full set of parameters for each task, $u^{(l)}$ represents the partial set of parameters unique to each task, $v^{(l)}$ represents the low-rank subspace, and $\Theta^{T} \in \Re^{k \times d}$ is the low-rank parameter matrix shared by all tasks. The task clustering approach utilises the idea of data clustering, where similar tasks can be clustered into one class from a parametric perspective, so that a set of tasks can be classified into multiple classes, and it primarily utilises a Gaussian mixture model for task clustering [43, 46].

The linkage in the task-linked learning approach mainly reflects the correlation between tasks, including task variance and similarity [36]. Some researchers propose to extract prior knowledge of each task through a Gaussian process of multiple tasks a_j^i, with the function input as x_j^i, so $(x_j^i) \sim N(0, \Sigma)$. Where $a = (a_1^1, \ldots, a_n^m)^T$, the variance Σ is related to the variance between tasks. The multilevel approach in a simpler mode is to decompose the parameter matrix into two parts as in Equation (2) [9, 23].

$$W = U + V \tag{2}$$

In Equation (2), and are distributed to capture different parts of the task linkage, represents the overall parameters of a single model, and generally captures noise in multiple tasks through sparsity, or some outlier information. A more complex multi-level approach is to decompose the parameter matrix into multiple components, as in Equation (3) [7].

$$W = \sum_{i=1}^{m} W_i \tag{3}$$

In Equation (3), $m>2$, m indicates the parameter decomposition into parts. This research re-optimizes the SS return results for a SS on e-commerce platforms by automating the addition of personalized selling keyword SPs, thereby improving their appeal to users. Investigate the mechanism for adding personalized SP to sponsor search, the framework of which is shown in Figure 2.

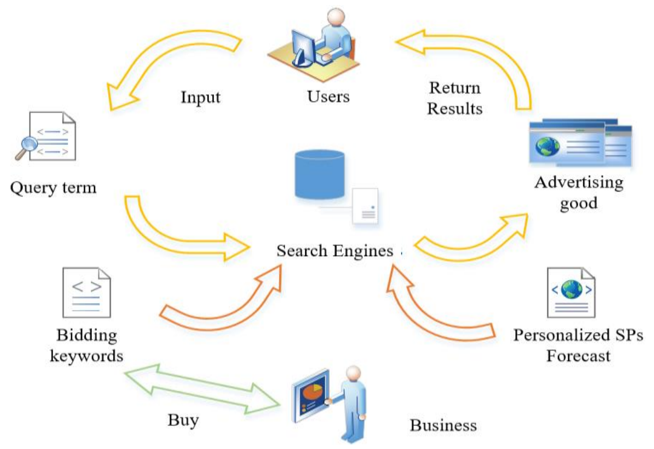


Figure 2. Mechanism diagram of adding personalized SPs to sponsorship search.

As can be seen from Figure 3, in SS, merchants bid for query keywords, and when a user sends a query request, the bidding mechanism is triggered and the winning advertised item is then displayed in the user search listings by adding SPs before its title through the research model [8, 33]. This research is based on the deep learning network model. The neural network model is trained by using the data of users clicking on the specific feature keyword SP. The basic model built is shown in Figure 3.

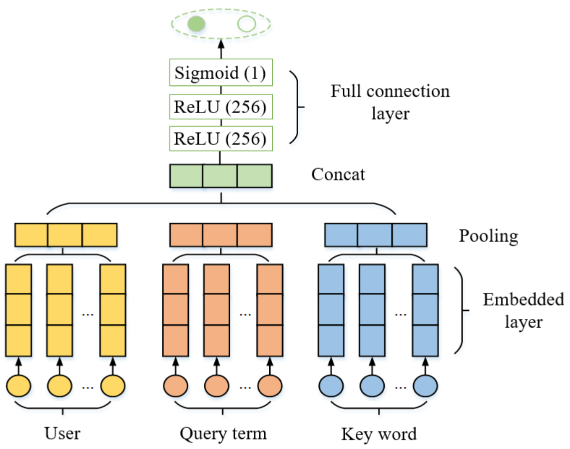


Figure 3. Basic model architecture.

In the input layer, the model has three parts, the user u, the query term q, and a specific feature keyword v. For a user u, the recent click history is used to characterize the vector u. At the embedding layer, the set of keywords studied w is a very large set due to the wide variety of items in the actual business scenario. The high-latitude vector of multi-hot representations first needs to be dimensioned down to use only a table of embedding vectors, which the embedding layer can transform into a low-density dense vector. Define $Em(w)$ as a lookup function that returns and embedding vector for the keyword w. The embedding layer transforms the user u, the lookup term q and the specific feature keyword v into the corresponding embedding representation.

Since both the user u and the query term q are collections of multiple keywords formed after word splitting, after passing through the embedding layer above, u and q are transformed into a vector representation of variable length. The ordinary deep neural network cannot accept the input in this case, so it needs to add a pooling layer on top of the model after the embedding layer. The research refers to SFs and SPs as SFs and SPs. The specific form of the pooling layer operation is shown in Equation (4) [21].

$$e_q = \frac{1}{s}\sum_{i=1}^{s} Em(w_i) \tag{4}$$

In Equation (4), e_q represents the average pooled query word column vector. After the pooling layer, the model adds a concatenation layer that stitches together the three parts of u, q, v information as in Equation (5).

$$x = \left[e_u^T, e_q^T, e_v^T\right]^T \tag{5}$$

In Equation (5), e_u, e_v is the average pooled column vector of users and keywords, respectively, and x is the stitched vector. The network can already compute such fixed-length dense vectors much faster when the x vectors incorporating information about users, query terms and SFs are obtained. It will be used as input to the fully connected layer later on, increasing the model expressiveness, as in Equation (6).

$$h^{(1)} = f\left(W^{(1)}x + b^{(1)}\right) \tag{6}$$

In Equation (6), $h^{(1)}$ represents the output of this fully connected layer and $W^{(1)}$, $b^{(1)}$ is the parameter of the fully connected layer. $f(.)$ denotes an arbitrary non-linear activation function [45, 49]. After that, if there are multiple layers, then the output of the previous layer is used as the input to the next layer, as in Equation (7) [30].

$$h^{(2)} = f\left(W^{(2)}h^{(1)} + b^{(2)}\right) \tag{7}$$

In Equation (7), $h^{(2)}$ represents the output of this fully connected layer and $W^{(2)}$, $b^{(2)}$ is the parameter of the next fully connected layer. The final output layer of the model is a simple one that outputs a value between 0 and 1 via a Sigmoid function, which can be considered as a probability value, as in Equation (8).

$$y' = \sigma\left(w^{(y)}h^{(2)} + b^{(y)}\right) = \frac{1}{1+\exp\left(-w^{(y)}h^{(2)} - b^{(y)}\right)} \quad (8)$$

In Equation (8), $W^{(y)}$, $b^{(y)}$ is the parameter of the output layer and y denotes the prediction value under an instance (u, q, v, y) is given. The training loss function for the Base Model (BM) under study is a standard supervised training with a standard cross-entropy loss function as shown in Equation (9) [16, 39].

$$\iota = \frac{1}{\left|S^{SF}\right|} = \sum\left[y\log y' + (1-y)\log\left(1-y'\right)\right] \quad (9)$$

In Equation (9), $|S^{SF}|$ represents the number of sample instances in S^{SF}, y represents the predicted values, the summation operation is to add up the results of all the sample instances in S^{SF}, and ^{l} represents the loss function.

3.2. Design of an Enhanced Multi-Task Learning Algorithm-Based Intelligent Push Model for Personalized Advertising in E-Commerce

Compared to the click logs of users clicking on SFs, the click-through rate CTR data of users clicking on products in search engines is richer and the keywords in the product titles are more comprehensive and can cover more SPs [29, 34]. When users view products, they are more likely to be attracted to the titles of the products because the style of SPs displayed in these titles is more compelling. The architecture of the model based on multi-task deep learning is shown in Figure The model architecture based on multi-task deep learning is shown in Figure 4 [37].

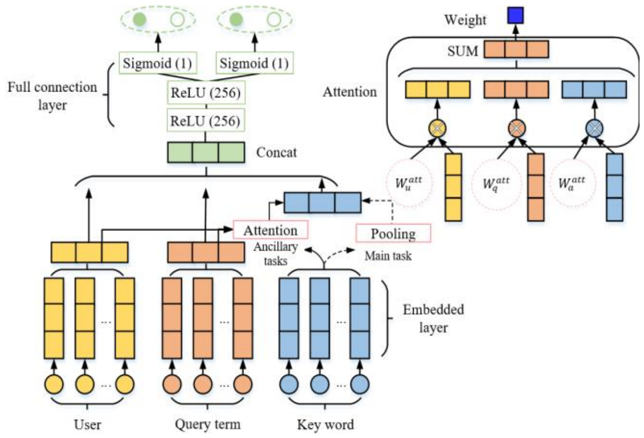


Figure 4. Architecture of multi-task deep learning model.

As can be seen from Figure 4, the research model uses a hard parameter sharing mechanism. The overall architecture of the model is relatively similar to the BM, but there are two main differences in it, one being that the output layer of the model is separate for the primary and secondary tasks. The second is that the model accepts the same input module for SPs and SFs as the advertised item title as input, but replaces the pooling module with an attention module for the secondary task [32, 42]. An intuition about the attention mechanism is that since the title of the item is composed of multiple key words that express multiple characteristics of the item, it is very similar to SPs and SFs. This is expressed in Equation (10).

$$S^{C} = \left\{\left(u, q, a, y^{c}\right)\right\} \quad (10)$$

In Equation (10), S^C represents the log data of a user clicking on a product with a label. Where $a \in \gamma$ represents an advertised item and y^c represents a 0/1 binary label indicating whether the user u clicked on a.

An attention module helps to extract the relatively important key words in the headlines to explain the corresponding click behavior. It also makes the output distribution of the pooling layer a more compatible match between the two tasks. Firstly, $D^a=\{d_1, d_2, \ldots, d_n\}$ is defined as the set of keywords, derived from the headline split of the advertised product a. The study employs a more widely used attention mechanism, expressed as in Equation (11) [26].

$$b_j = z^T \tanh\left(W_u^{att} e_u + W_q^{att} e_q + W_a^{att} Em\left(d_j\right)\right) \quad (11)$$

In Equation (11), represents the parameters of the first layer network and W_u^{att}, W_q^{att}, W_a^{att} e_u, e_q is the vector representation of the user and the query term. z^T is the second layer of network parameters, and b_j represents the weight score of d_j. The final normalization is performed by a layer of SoftMax layers, as in Equation (12).

$$\alpha_j = \frac{\exp\left(b_j\right)}{\sum_{i=1}^{n} \exp\left(b_i\right)} \quad (12)$$

In Equation (12), α_j represents the corresponding attention weights, which are finally combined with $Em(d_j)$ to make a weighted sum, as in Equation (13).

$$e_a = \sum_{j=1}^{n} \alpha_j Em\left(d_j\right) \quad (13)$$

In Equation (13), e_a represents the final vector representation needed for the a title. This is because the desire to extract the most important words in the title is related to the user's own preferences as well as the currently entered query term. The study therefore adds the influence of the user and the query term to the attention mechanism as a way to enhance the personalized prediction. Regarding the loss function of the study model, both tasks are binary cross-entropy loss functions, and the loss function for the main task is shown in Equation (14) [11].

$$\iota_{main} = \frac{1}{\left|S^{SF}\right|}\sum\left[y\log y' + (1-y)\log\left(1-y'\right)\right] \quad (14)$$

In Equation (14), l_{main} denotes the loss function for the primary task and $|S^{SF}|$ denotes the number of sample instances in S^{SF}. Similarly, the loss function for the auxiliary task is shown in Equation (15).

$$l_{aux} = \frac{1}{|S^C|}\sum\left[y^c \log\left(y^c\right)' + \left(1-y^c\right)\log\left(1-y^c\right)'\right] \quad (15)$$

In Equation (15), l_{aux} denotes the loss function of the auxiliary task, (y^c) denotes the labels of the sample instances in S^C, and $|S^C|$ denotes the number of sample instances in S^C. The model training approach proposed in the study differs from the classical MTL model applicable to joint learning. For joint learning training, it means that the classical multi-task deep learning model is trained with the same sample instances as input for one small batch update for multiple tasks [19, 44]. Multiple tasks share the same input source, and then multiple tasks output different results simultaneously. However, the two tasks of the study do not share the same input source, but rather (u, q, v) and (u, q, a). Therefore, the study proposes two types of training, namely pre-training and alternate training. The algorithm steps for alternating training are shown in Algorithm (1).

Algorithm 1: Alternate Training Algorithm.

Step 1: Random initialize the model parameters
Step 2: For iteration in 1, 2, .., do
Step 3: Select the data source of the primary task or secondary task with a probability ratio of 1:k
Step 4: if selects the main task then
Step 5: Take a small batch sample instance for S^c
Step 6: Calculated loss value
Step 7: Update model parameters
Step 8: end
Step 9: else
Step 10: Fetch from S^{SF} *a small batch sample instance*
Step 11: Calculated loss value
Step 12: Update model
Step 13: end
Step 14: Else

From Algorithm (1), the alternate training algorithm uses Θ_1/Θ_2 to represent the set of parameters associated with the secondary and primary tasks respectively. The model is trained iteratively by sampling small batches from the full training dataset, and at each iteration the data sources for the main and auxiliary tasks are randomly selected with a probability ratio of 1:k. Then, the relevant model parameters are updated by selecting small batches of data sets from the training set S^{SF} or S^C depending on the task. The study set the probability of the secondary task being selected to be k times that of the primary task because the dataset size of S^C is usually larger than that of S^{SF}. The criterion for setting k is to allow both data sources, the primary and secondary tasks, to perform roughly the same number of parameter iterative updates when the algorithm stops iterating. This ensures that the model can be adequately trained with both datasets. The steps of the pre-training algorithm are similar to those of the alternate training algorithm. The essence of the pre-training strategy is to perform migration learning from the auxiliary task to the main task. The study uses the dataset S^C to train the parameters of the auxiliary task model alone, and after the model has converged to obtain the set of parameters already trained Θ_1. These already trained parameters are then used as prior knowledge. The model for the main task overloads these trained parameters and is further fine-tuned using the dataset S^{SF}. As shown in Figure 6, it is the intelligent push process of e-commerce personalized advertisement based on the enhanced MTL algorithm.

Ultimately, the study of an enhanced MTL algorithm-based intelligent push model for personalized advertising in e-commerce is shown in Figure 7. As can be seen in Figure 7, the model is essentially the same as the model based on multi-task deep learning. However, additional features about the user and the query term are added at the input layer to more comprehensively consider the personalization of the user. In the enhanced MTL model framework, features are characterized in multiple groups in the form of multi-hots. Each group contains multiple discrete features or semantic features represented as bags of words. A "{}" is used as a group separator; a ";" is used as a separator for different features within a group. Multiple groups of multi-hot encoded representations of vectors of features are used as input to the embedding layer of the model, and fixed-length vectors are output as input to the fully-connected layer of the model via the embedding and pooling layers, so that pooling operations are performed within each group.

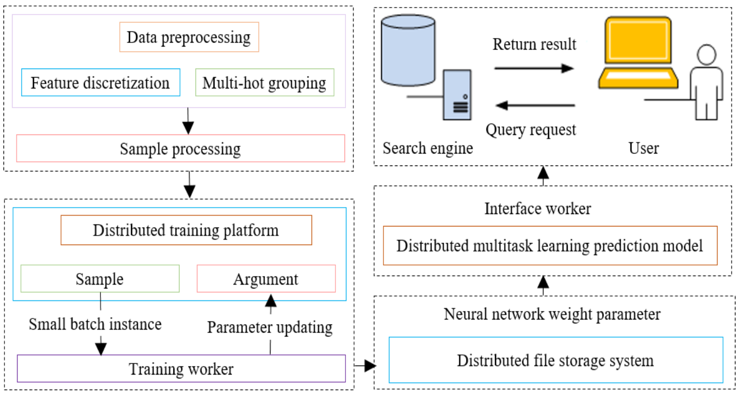


Figure 6. Intelligent push process of e-commerce personalized advertisement based on enhanced multi-task learning algorithm.

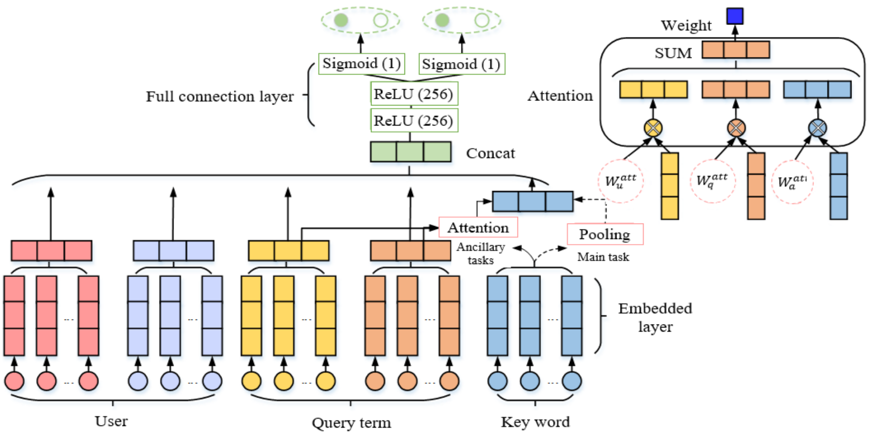


Figure 7. Intelligent push model of e-commerce personalized advertising based on enhanced multi-task learning.

4. Analysis of Experimental Results of an Intelligent Push Model for Personalized Advertising in E-Commerce Based on Multi-Task Learning Algorithms

The model proposed in the study is done on the TensorFlow RS, or TFRS, platform. The study proposes to optimize the SS return results by adding personalized SPs to enhance its appeal to users. To verify its effectiveness, the experiments follow the standard A/B testing principle, where search traffic from a real-life scenario on a shopping website is equally divided into a base bucket and a test bucket. As the study used the hit rate CTR as a measure to assess how attractive the SS return results were to the users. Thanks to the large traffic size of the shopping site, the experiment can yield more convincing results. Typically, an increase in CTR above 0.3% is considered a significant increase on this site. The experiment will also use p-values to distinguish whether the results are significant or not. The results of the experiment with the addition of personalized SPs are shown in Table 2.

Table 2. Comparison of experimental results of adding personalized SPs.

Experiment	Basic barrel	Test barrel	CTR relative lift (%)	P	Total display
No.1	TSS	PSPSS	+10.3	0.00001	30,516,000
No.2	NSPSS	PSPSS	+5.76	0.0009	40,942,000
No.3	No highlight	Highlight SPs	+5.67	0.0166	30,500,000
No.4	Add 2 SPs	Add 3 SPs	+4.10	0.7347	21,490,000
No.5	Add 2 SPs	Add 1 SPs	+4.84	0.001	20,200,000

*P < 0.05 difference is significant.

Firstly, as can be seen from Experiment 1 in Table 2, compared to the original headline-based SS results in TSS, the test bucket is a significant increase in the CTR of the advertised item by adding personalized SPs, i.e. PSPSS, where the CTR is increased by a relative 10.3%. In experiment 2, both the base bucket and the test bucket were ad item headline displays with SPs, but the SPs in the base bucket did not consider user personalization. From the data, the relative increase in CTR in experiment 2 by changing only the personalization factor was 5.76%, with a P =0.0009 also indicating a significant increase. Compared to the non-personalized SPs generated by NSPSS, the personalized SPs generated by PSPSS can better engage the target users. From experiment 3, it can be seen the highlighted SPs helped to increase the click-through rate of the AD project by 5.67%, with a P-value of 0.0167. As you can see from experiments 4 and 5, the result of adding two SP is much better than the result of adding only one sp. The experimental results show that displaying only one SPs is not reliable, and displaying two SPs is the safest and most reliable method. The results show that the strategy based on SPs is reliable.

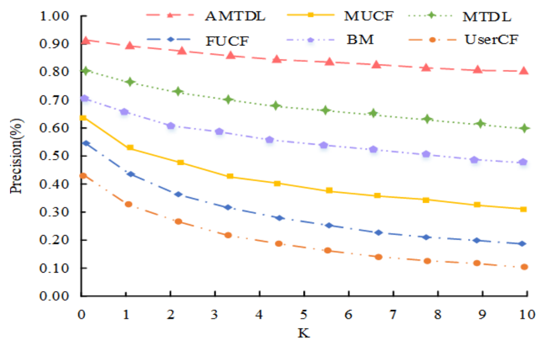
The SF dataset was used to train the proposed BM with 47356000 sample instances, and the SF dataset was divided into four parts, based on the number of user clicks in the primary and secondary task datasets. The BM was trained using only the log data of user clicks on SFs as training data, referred to as the BM; the Multi-Task Deep Learning-Based Model (MTDL-BM) was trained using both the SF dataset and the AD dataset, referred to as the MTDL; and the MTL model was extended by adding additional features, referred to as the AMTDL. dataset by sampling the number of clicks that can roughly divide the SF dataset as the boundaries for dividing the dataset, and the AUC results for the three models are shown in Table 3.

Table 3. Comparison of AUC results of BM, MTDL and AMTDL under different hits.

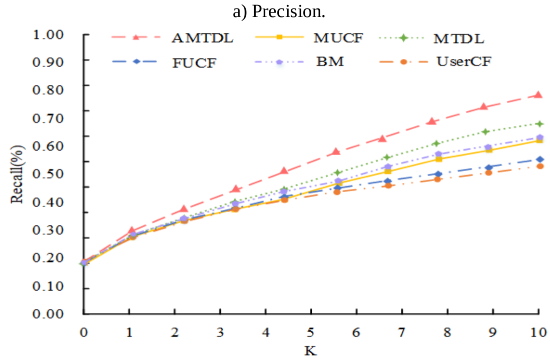
Hits		AUC (%)		
Main task	**Ancillary tasks**	**BM**	**MTDL**	**AMTDL**
≤ 6	> 21	0.7808	0.8805	0.9332
≤ 6	≤ 21	0.7076	0.8705	0.9128
> 6	> 21	0.6907	0.8461	0.8730
> 6	≤ 21	0.6851	0.8235	0.8586

As can be seen from Table 3, the greatest improvement in model effectiveness is seen in the set of ≤6 clicks for the primary task and ≤6 clicks for the secondary task. This indicates that if users have rich click behavior on the secondary task but only sparse click behavior on the primary task, then the study's MTL model is most appropriate for this dataset and can deliver the greatest improvement. Secondly, the AUC values of the studied AMTDL model improved by 15.24% and 5.27% over the BM and the MTL model MTDL respectively. All in all, it shows that the MTL AMTDL model is the most suitable for this type of data set and can bring the greatest improvement in accuracy.

To further validate the performance of the research model, the experiments were conducted by noting the traditional user-based collaborative filtering as User CF, this association rule-based collaborative filtering algorithm as FUCF, followed by the hybrid algorithms of TEUCF and TAUCF for associated and unassociated users respectively as MUCF algorithm. The accuracy and recall rates of the six algorithms were measured by varying the number of recommended ads K as evaluation metrics. The results are shown in Figure 8.



a) Precision.

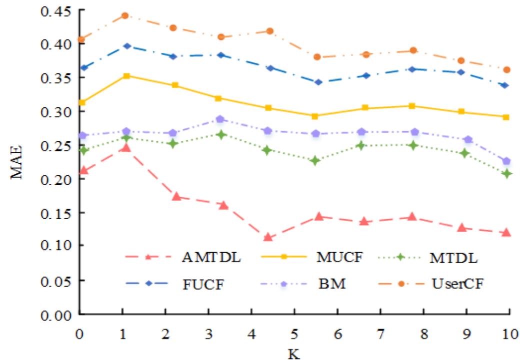


b) Recall curve.

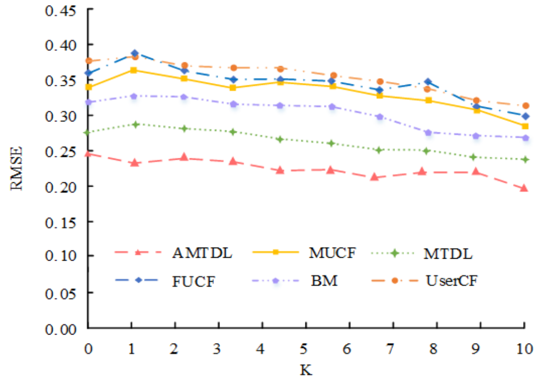
Figure 8. Accuracy and recall results of each recommendation model under different K values.

As can be seen from Figure 8-a), the studied AMTDL model has a significantly higher accuracy rate than the other algorithms, with an accuracy rate of 93.2% when the number of recommended ads is 1. As the number of advertisements increases, the accuracy of all six models decreases, and the AMTDL model is still the one with the smoother decreasing arc. As can be seen from Figure 8-b), in terms of recall rate, the curves of these six models are basically the same when the K value is 1-3. After the K value reaches 6, the recall rate of the AMTDL model is significantly higher than the other models, and the upward trend is more obvious. The experiments show that the AMTDL model constructed by the study outperforms other traditional recommendation models and their BMs in terms of both accuracy and recall.

The experiments then used Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) as evaluation metrics to measure the effectiveness of the recommendations. MAE and RMSE are based on the magnitude of the difference between the user ratings of the ads predicted from the training set and the user ratings on the actual test set, with smaller coefficients indicating smaller errors and more accurate recommendations. Experiments were conducted by varying the number of recommended ads K. The results are shown in Figure 9.



a) MAE curve.



b) RMSE curve.

Figure 9. MAE and RMSE results of each recommended model under different K values.

As can be seen from Figure 9-a), the MAE of the studied AMTDL model increases when the number of recommended ads is 2, just like the other algorithmic models, but overall, the MAE of this model is the smallest among all algorithmic models, and the MAE is the smallest when the number of recommended ads is 5, which is 0.174. As can be seen from Figure 9-b), in the RMSE coefficient, the curve of the AMTDL model is always the mean value of the RMSE is 0.2012, indicating that its scoring accuracy is higher than all the other algorithmic models.

In addition to the commonly used accuracy recall and RMSE and MAE coefficients, coverage is a better indicator of whether the recommendations can avoid the popular ones and recommend some more distinctive "cold" ads. Therefore, the experiments used coverage as a metric, and the coverage coefficients obtained from different algorithms by varying the number of recommended ads K are shown in Figure 10.

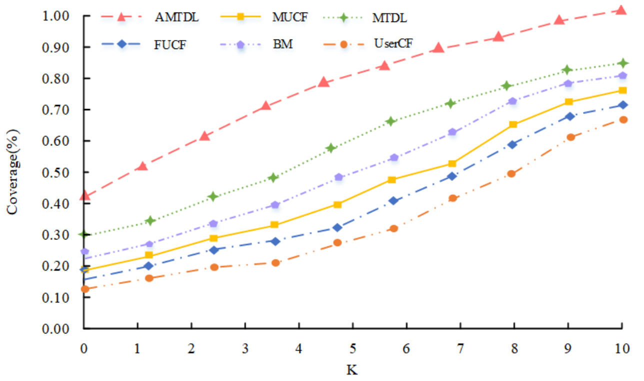


Figure 10. Coverage curve.

As can be seen from Figure 10, the coverage rate of each algorithm model continues to grow as the number of recommended ads increases, and the coverage rate of the AMTDL model is always higher than the other algorithm models, and its growth rate is larger, and its coverage rate is 97.4% when the number of recommended ads reaches 10. This suggests that it is more valuable to study enhanced MTL algorithms for personalized ad push models for e-commerce.

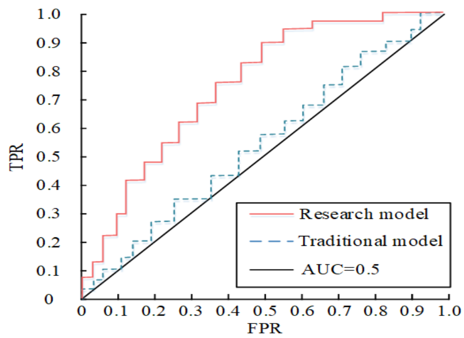
In order to verify the prediction performance of the research model better, the prediction accuracy and RMSE of the research model are compared with other advanced models. This includes the Dynamic Multi-Pathing-Distributional Gradient Boosting Machines (DMP-DGBM) model based on the developed gradient propulsion technology, which is constructed by replacing its kernel (i.e., decision tree function) with a multi-parameter optimization function [3]. A predictor is constructed based on LSTM method, and the Long Short-Term Memory-Particle Swarm Optimization (LSTM-PSO) model is identified by using the functional PSO algorithm to identify the optimal structure and parameter values of the network [4]. Based on the concept of intelligent data mining, the Water quality scale prediction model (IM12CP-WQI) is constructed by combining DMP-BAT algorithm and DMARS algorithm [2]. In addition, the matrix code is constructed for the connecting edge by using FFGM, and the matrix is transformed into the correlation matrix, and the intelligent deep analysis algorithm of Frequency Reduction bast (RF-FFGM) based on FFGM is established [14]. The result is shown in Table 4.

Table 4. Comparison of prediction performance of 5 models.

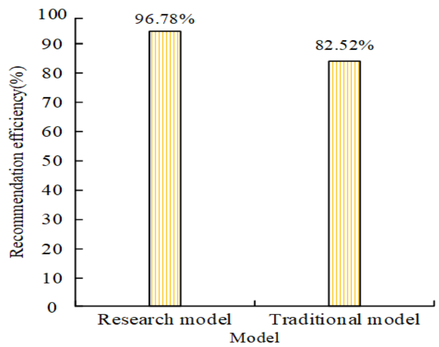
Method	Recall	Accuracy	F1-score	RMSE
DMP-DGBM [3]	0.675	0.857	88.2	0.438
LSTM-PSO [4]	0.732	0.860	89.7	0.419
IM12CP-WQI [47]	0.819	0.893	90.1	0.376
RF-FFGM [14]	0.886	0.921	93.5	0.320
Research algorithm	0.912	0.953	96.8	0.216

As can be seen from Table 4, in terms of recall rate, the recall rate of the research algorithm is 91.2% higher than that of the other four algorithms. In terms of accuracy, the accuracy of the research method is 95.3%, which is still higher than other four methods. In terms of F1 score, the research algorithm is 8.6, 7.1, 6.7 and 3.3 higher than DMP-DGBM, LSTM-PSO, IM12CP-WQI and RF-FFGM, respectively. In terms of root-mean-square error prediction, the root-mean-square error of the research method is still the smallest in the 5 algorithms, only 0.216. In summary, compared with the current advanced model, the research method has certain advantages.

As shown in Figure 11, the performance comparison between the recommendation model designed for the study and the current popular recommendation model.



a) Comparison of model ROC.



b) Comparison recommendation efficiency of model.

Figure 11. Comparison of recommendation performance of recommendation models.

As can be seen from Figure 11-a), the AUC value of the traditional recommendation model is 0.83. The curve area AUC of the recommended model of the improved MTL algorithm constructed in this study is 0.92. As can be seen from Figure 11-b), the recommendation efficiency of the research model is 96.78%, which is 14.26% higher than that of the traditional model. To sum up, compared with the traditional advertising recommendation model, the research model has a good advantage in the performance of personalized advertising recommendation.

5. Discussion

A large-scale online A/B test is carried out systematically to prove the feasibility of personalized optimization of advertising content proposed in this paper. To address the lack of explicit feedback on user preferences, this paper trains the model using a dataset of user clicks on SFs as basic facts about user preferences for SPs. The highlighted SPs helped increase the click-through rate of the AD item by 5.67%, with a P-value of 0.0167. The result of adding two SP is much better than the result of adding only one sp. The results show that the strategy based on SPs is reliable. CTR prediction data is integrated into the basic model as an auxiliary task to enhance the effectiveness of personalized SPs prediction tasks. When the number of clicks of the main task is ≤6 and the number of clicks of the second task is ≤6, the effectiveness of the model is improved the most. This suggests that if users have rich click behavior on secondary tasks and only sparse click behavior on primary tasks, then the study's MTL model is best suited for that dataset and can provide the greatest improvement. Additional features about users and query terms are also explored and integrated into the MTDL model, which is further extended into an enhanced multitasking learning AMTDL model. Experiments show that the AUC value of the AMTDL model is 15.24% and 5.27% higher than that of the basic model BM and the MTL model MTDL, respectively. Finally, this paper conducts experiments online and offline through large-scale Taobao data sets. The AUC value of the traditional recommended model is 0.83. The Recommended Curve Area AUC of the improved MTL algorithm constructed in this study is 0.92. In terms of accuracy, the accuracy of the research method is 95.3%, which is still higher than the other four methods. In terms of F1 score, the research algorithm is 8.6, 7.1, 6.7 and 3.3 points higher than DMP-DGBM, LSTM-PSO, IM12CP-WQI and RF-FFGM, respectively. In terms of root-mean-square error prediction, the root-mean-square error of this method is still the smallest among the five algorithms, only 0.216. This shows that this research method has certain advantages compared with the current advanced models. The recommendation efficiency of the research model is 96.78%, which is 14.26% higher than that of the traditional model. To sum up, compared with the traditional advertising recommendation model, the research model has a good advantage in the performance of personalized advertising recommendation.

6. Conclusions

To improve the personalized recommendation effect of e-commerce platform advertisements, this paper builds an intelligent push model based on MTL algorithm. The experimental results show that the addition of personalized SP significantly increases the click-through rate of advertisements, up to 10.3%. Highlighting SP increased click-through rates by 5.67%, and adding two SP was better than adding one SP. The AMTDL model in the study performed well when the main task was clicked less, and compared with BM and MTDL models, the AUC value increased by 15.24% and 5.27%, respectively. In addition, the accuracy of AMTDL model is 93.2%, the recall rate and scoring accuracy are also higher than other models, the RMSE average is 0.2020, and the coverage rate reaches 97.4% when K=10, showing a strong performance advantage. However, as the data from the study is mainly derived from specific e-commerce platforms, it may not be fully applicable to other types of e-commerce platforms or markets with different user groups. Although the dataset covers a large number of users clicking behaviors, these samples are mainly focused on one product or user group. To address the above limitations, future research can ensure the universality of the model by expanding the sources of the dataset to include other e-commerce platforms or transnational markets. And consider adding more diverse user behavior data to the dataset, especially those with different cultural backgrounds or shopping habits, to improve the generalization ability of the model. Reinforcement learning or transfer learning methods can be introduced to better adapt to diverse needs in different data contexts. In addition, more complex MTL models can be designed to improve the adaptability of the models in different tasks and data environments through soft parameter sharing mechanism.

Authors' Contributions

Min Hou Writing-original draft preparation; Yizhou Zhang Methodology, Mengze Zhang Writing-review and editing.

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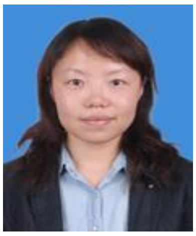

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